Narrow-Band Interference Rejection in DS/CDMA Systems Using Adaptive (QRD-LSL)-Based Nonlinear ACM Interpolators

Jenq-Tay Yuan and Jenq-Nan Lee

***Abstract*—An Mth order adaptive *lattice filter* automatically generates all M of the outputs that would be provided by M separate transversal filters. This feature may effectively suppress the narrow-band interference (NBI) of either unknown or time-varying bandwidth (or number of frequency bands) in direct-sequence code-division multiple access systems for which the order of the interference rejection filter that achieves the optimal performance is unknown or constantly changing. Moreover, a lattice filter may significantly outperform its transversal counterpart in complex jamming environments in which the adaptive lattice filter must suppress multiple jammers, since each stage of a lattice filter adapts to suppress an *orthogonal component* of the NBI.**

This paper develops a computationally efficient and numerically stable adaptive QR-decomposition-based least squares lattice (QRD-LSL)-based nonlinear approximate conditional mean interpolator to suppress NBI effectively. Simulation results demonstrate that both the signal-to-noise ratio improvements and the convergence rate achieved by the proposed interpolators outperform those of other existing prediction-based techniques.

***Index Terms*—Approximate conditional mean (ACM) nonlinear filter, code-division multiple access (CDMA), interpolation filters, lattice structure, least mean square (LMS)-based filters, narrow-band interference (NBI) suppression, prediction filters, predictors, QR-decomposition-based least squares lattice (QRD-LSL) interpolators.**

I. INTRODUCTION

NARROW-BAND interference (NBI) suppression utilizes the discrepancy in the predictability between the interference and the spread-spectrum (SS) signal in that the former can be accurately predicted (or interpolated), whereas the latter is wide-band and hence unpredictable. Consequently, a *linear* prediction or interpolation of the received signal can be used to estimate the interference [1]. Vijayan and Poor [2] proposed a *nonlinear* least mean square (LMS)-based approximate conditional mean (ACM) predictor that could greatly outperform its linear counterpart. The rationale for the nonlinear ACM filter is based on the fact that the non-Gaussian measurement noise in the prediction requires a nonlinear transformation that takes the form of a soft-decision feedback attempting to estimate the NBI. Rusch and Poor [3] extended the nonlinear NBI techniques to multiple users in CDMA.

A lattice filter is known to be able to provide better dynamic performance than its transversal counterpart especially in complex jamming environments (e.g., multiple jammers) [4]. One highly desirable feature of a lattice filter is that it automatically generates all M of the outputs of different orders that would be provided by M separate transversal filters, where M is the order of the corresponding filter. This feature is useful in NBI suppression since, in practice, the order of the interference rejection filter that achieves the best performance is unknown to the receiver and may constantly change because the jammers' bandwidth or the number of nonoverlapping interference bands is either unknown or time-varying. Consequently, optimum removal of NBI may not be achieved using a fixed filter length. This paper develops an adaptive QR-decomposition-based least squares lattice (QRD-LSL)-based *nonlinear* ACM interpolator whose computational complexity is only $O(M)$ per iteration to effectively suppress NBI. The proposed interpolator facilitates dynamic assignment and rapid automatic determination of the most effective filter length. Optimum removal of strong NBI of unknown (or time-varying) bandwidth or NBI of an unknown number of frequency bands may therefore be achieved.

II. NONLINEAR ACM FILTERS FOR NBI IN DS-CDMA SYSTEMS

A. System Model

The spread-spectrum and NBI model used herein is the same as that used in [3]; that is, the received signal is given by $z(k) = s(k) + n(k) + i(k)$, where the ambient white noise $n(k)$ can be modeled as white Gaussian noise with variance σ_n^2, and interference $i(k)$ is modeled as having a bandwidth much less than the spread bandwidth. The SS signal $s(k)$ is the sum of N independent, equiprobable, binary, and antipodal random variables, where N is the number of users in the direct-sequence code-division multiple access (DS-CDMA) system. Vijayan and Poor [2] modeled the NBI as a Gaussian autoregressive (AR) process of order q, i.e., $i(k) = \sum_{j=1}^{q} \phi_j i(k-j) + u(k)$, where $\phi_1, \phi_2, \ldots, \phi_q$ are AR parameters and $\{u(k)\}$ is a white Gaussian process. Notably, although this model is designed mainly to enable the interference suppression filter to suppress an AR interferer, our simulation results show that the interference suppression filter still very successfully combats tone jammers, because a sinusoidal signal can be modeled by an

Manuscript received June 2, 2001; revised May 3, 2002. This work was supported by the National Science Council, Taiwan, R.O.C., under Contract NSC 91-2213-E-030-015.

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Digital Object Identifier 10.1109/TVT.2002.808808

AR(2) process [5, pp. 199, 140]. Furthermore, a narrow-band digital communication signal may be approximated by an AR process of sufficiently large order, since the power spectral density (PSD) of a narrow-band digital communication signal may be approximated by that of an autoregressive-moving average (ARMA) process. Consequently, by modeling the NBI as a Gaussian AR process, the resulting interference suppression filter of a sufficiently large filter order may still be useful in combating digital NBI that has its relevance in the field of overlay applications.

B. Nonlinear ACM Filter

By considering a system with N CDMA users and assuming that all users are received with the same (unit) power, the density of the measurement noise can be shown to be $p[v(k)] = 2^{-N}\sum_{j=1}^{N}\binom{N}{j}N_{\sigma_n^2}[v(k)-N+2j]$, which is highly non-Gaussian. If the received signal $z(k) = i(k) + v(k)$ is used directly as the input to the predictors, $v(k) = s(k) + n(k)$ severely degrades the performance of interference rejection of $i(k)$. Therefore, an optimal filtered estimate of the interference $i(k)$ based on the observations $Z^k = \{z(1), z(2), \ldots, z(k)\}$, $\hat{i}(k)$, referred to herein as *interference estimate,* must be obtained and then used as the input to the predictors instead. By assuming that the prediction density $p[i(k)|Z^{k-1}]$ is Gaussian, given Z^k, with non-Gaussian measurement noise $v(k)$, $\hat{i}(k) = E\{i(k)|Z^k\}$ can be obtained by employing a nonlinear transformation. Consider an $(m+1)$st-order linear predictor whose input is $\hat{i}(k)$. The output of the predictor is $\bar{i}(k) = \hat{\mathbf{i}}_{m+1}^T(k-1)\mathbf{a}_{m+1}(k)$, referred to herein as *interference prediction,* where $\hat{\mathbf{i}}_{m+1}^T(k-1) = [\hat{i}(k-1), \hat{i}(k-2), \ldots, \hat{i}(k-m-1)]$ and $\mathbf{a}_{m+1}^T(k) = [a_{m+1,1}(k), a_{m+1,2}(k), \ldots, a_{m+1,m+1}(k)]$ represents the tap-weight vector of the linear predictor at time k. Therefore, the prediction error $\varepsilon(k)$ that represents observation less the interference prediction can be expressed as $\varepsilon(k) = z(k) - \bar{i}(k) = [i(k) - \bar{i}(k)] + v(k) = e(k) + v(k)$, where $e(k)$ is the prediction error less the soft-decision on the spread-spectrum signal. Previous investigation [3] has indicated that the nonlinear transformation that transforms the prediction error $\epsilon(k)$ to produce the optimal $e(k)$ is given by

$$\hat{e}(k) = \rho[\varepsilon(k)] = \varepsilon(k) - N + 2 \cdot \frac{\sum_{l=1}^{N} l \binom{N}{l} e^{-[\varepsilon(k)-N+2l]^2/2\sigma_k^2}}{\sum_{j=0}^{N}\binom{N}{j} e^{-[\varepsilon(k)-N+2j]^2/2\sigma_k^2}}, \quad N \geq 1$$

where $\sigma_k^2 = E\{\varepsilon^2(k)\} - N$. The interference estimate can then be obtained by $\hat{i}(k) = \hat{e}(k) + \bar{i}(k)$.

III. Adaptive (QRD-LSL)-Based Nonlinear ACM Interpolators for NBI Suppression

A. Order-Recursive LSL Interpolators of Order (p, f)

When a (p, f)th-order linear interpolation is used to achieve interference rejection, the interference estimate $\hat{i}(j)$ is interpolated from p past and f future neighboring interference estimates, that is, $\hat{i}_{p,f}(j) = -\sum_{l=-p, l\neq 0}^{f} b_{(p,f),l}(k-f)\hat{i}(j+l)$, $1-f \leq j \leq k-f$, where $b_{(p,f),l}(k-f)$ is the interpolation coefficient at time k. The (p, f)th-order interpolation error at each time unit can then be defined as $e_{p,f}^I(j) = \hat{i}(j) - \hat{i}_{p,f}(j)$, $1-f \leq j \leq k-f$. Herein, we refer to any Mth-order interpolation filter that operates on the present interference estimate as well as p past and f future interference estimates to produce the (p, f)th-order interpolation error at its output as a (p, f)th-*order interpolator,* where the order $M = p + f$ is assumed implicitly. If the most recent interference estimate used is $\hat{i}(k)$, then the optimum interpolation coefficients in $\hat{i}_{p,f}(j)$ can be determined by minimizing $\sum_{j=1-f}^{k-f}[e_{p,f}^I(j)]^2$. Yuan [7] developed *order-recursive LSL interpolators* that require only $O(M)$ operations by utilizing a modified version of linear forward and backward predictions, referred to as the *intermediate forward and backward predictions*. Because of the order-recursive structure, a (p, f)th-order LSL interpolator automatically generates all M of the outputs that would be provided by M separate transversal interpolators of all lower orders, so that the filter order may be adjusted at any time step. As an example, when the sequence BFBFBF... is used, the M outputs are provided by the M separate transversal interpolators of order (1,0), (1,1), (2,1), (2,2), ..., $(p-1, f-1)$, $(p, f-1)$, and (p, f). This modular structure facilitates dynamic assignment and rapid automatic determination of the most effective filter length. Consequently, optimum removal of strong NBI of unknown (or time-varying) bandwidth or NBI of an unknown (or time-varying) number of frequency bands may be achieved. Moreover, the LSL interpolator may be especially suitable in *complex jamming environments* in which it must suppress multiple jammers (e.g., in a CDMA environment) since each stage of the LSL interpolator adapts to suppress an *orthogonal component* of NBI. Fig. 1 presents a signal-flow graph of an *adaptive nonlinear ACM filter* that employs the (2,2)th-order QRD-LSL interpolator using the sequence BFBF.

B. Adaptive (QRD-LSL)-Based Nonlinear ACM Interpolators

As mentioned in Section II, an $(m+1)$st-order predictor is used to compute the interference estimate $\hat{i}(k)$. The optimum tap-weight vector $\mathbf{a}_{m+1}(k)$ of the $(m+1)$st-order predictor can be obtained by minimizing the sum of weighted forward prediction-error squares for $1 \leq j \leq k$, $\mathbf{E}^F = \sum_{j=1}^{k}\lambda^{k-j}[e_{m+1}^F(j)]^2$, where $e_{m+1}^F(j) \triangleq \hat{e}(j) = \hat{i}(j) - \bar{i}(j)$, $1 \leq j \leq k$, and $0 \ll \lambda \leq 1$ is the forgetting factor. Since successive stages of a lattice predictor are decoupled [6, p. 651], accordingly, by using the mutually uncorrelated (orthogonal) backward prediction errors produced by the QRD-LSL (lattice) predictor as tap inputs that are applied to a corresponding set of *regression coefficients* (to be determined), we may compute the interference prediction $\bar{i}(k)$ in a highly efficient manner. It is well known that a sequence of LS uncorrelated backward prediction errors is given by

$$\begin{aligned}\mathbf{e}_{m+1}^B(j-1) &= \left[e_0^B(j-1), e_1^B(j-1), \ldots, e_m^B(j-1)\right]^T \\ &= \mathbf{L}_{m+1}(k-1)\hat{\mathbf{i}}_{m+1}(j-1)\end{aligned}$$

where $\mathbf{L}_{m+1}(k-1)$ is the $(m+1)\times(m+1)$ lower triangular transformation matrix [6, p. 652]. Since both $\mathbf{e}_{m+1}^B(j-1)$

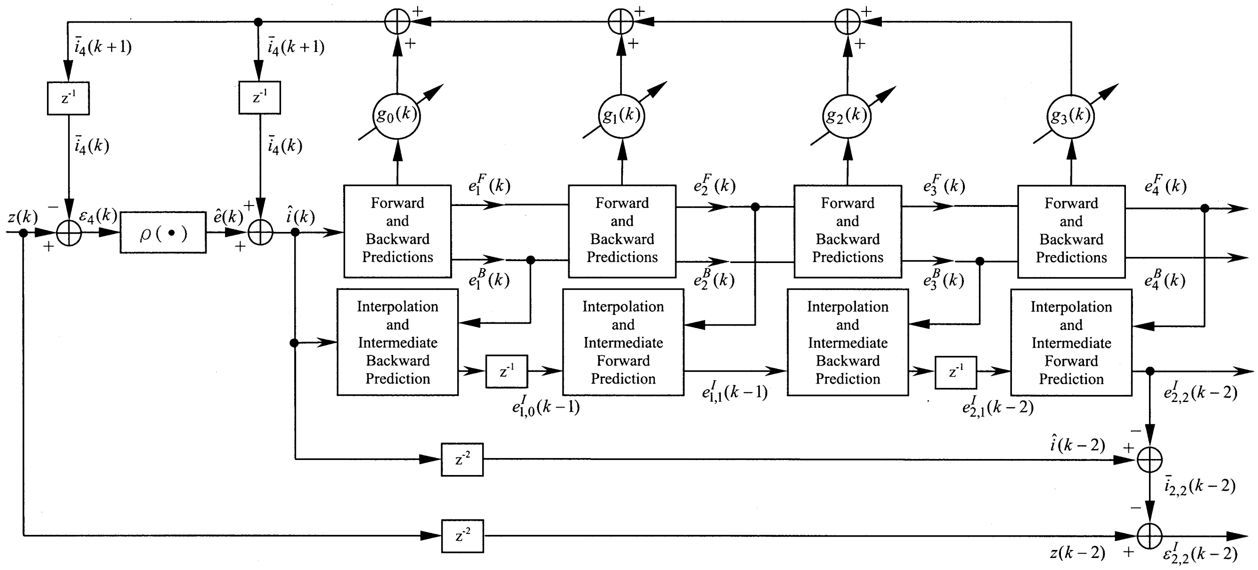

Fig. 1. Adaptive (QRD-LSL)-based nonlinear ACM interpolator using sequence BFBF.

TABLE I
SUMMARY OF THE (QRD-LSL)-BASED NONLINEAR ACM INTERPOLATION ALGORITHM

(I) Initializations (including those in the QRD-LSL interpolation algorithm in [7, Table II]):

$\bar{i}_M(1) = 0$

(II) Computations:

For $k = 1, 2, 3, \ldots$

$\varepsilon_M(k) = z(k) - \bar{i}_M(k)$

$\hat{e}(k) = \rho[\varepsilon_M(k)]$

$\hat{i}(k) = \hat{e}(k) + \bar{i}_M(k)$, where $\hat{i}(k)$ is the input of the QRD-LSL interpolator

$e_{0,0}^I(k) = e_0^F(k) = e_0^B(k) = \hat{i}(k)$

Call QRD-LSL predictions subroutine (see [7, Table II])

$$g_m(k) = \frac{e_m^F(k) - e_{m+1}^F(k)}{e_m^B(k-1)}, \quad m = 0, 1, \cdots, M-1$$

$$\bar{i}_M(k+1) = \sum_{i=0}^{M-1} g_i(k) e_i^B(k)$$

Call QRD-LSL interpolations subroutine (see [7, Table II])

$\varepsilon_{p,f}^I(k) = z(k-f) - \hat{i}(k-f) + e_{p,f}^I(k-f)$

End

and $\hat{\mathbf{i}}_{m+1}(j-1)$ contain exactly the same information, the predicted value of $\hat{i}(j)$ based on its $(m+1)$ previous interference estimates in $\hat{\mathbf{i}}_{m+1}(j-1)$ can also be computed by using the mutually uncorrelated backward prediction errors produced at the various stages of the QRD-LSL predictor, i.e., $\bar{i}(j) = \mathbf{a}_{m+1}^T(k)\hat{\mathbf{i}}_{m+1}(j-1) = \mathbf{g}_{m+1}^T(k)\mathbf{e}_{m+1}^B(j-1)$, where $\mathbf{g}_{m+1}^T(k) = [g_0(k), g_1(k), \ldots, g_m(k)]$ is the regression coefficient vector at time k. Consequently, the QRD-LSL predictor for NBI suppression can also be implemented by minimizing $\mathbf{E}^F = \sum_{j=1}^{k} \lambda^{k-j}[\hat{i}(j) - \mathbf{g}_{m+1}^T(k)\mathbf{e}_{m+1}^B(j-1)]^2$. It can be shown that the optimum value of the regression coefficients can be computed by $g_m(k) = ((e_m^F(k) - e_{m+1}^F(k))/(e_m^B(k-1)))$, $m = 0, 1, \ldots, M-1$, where $e_m^F(k)$, $e_m^B(k-1)$, and $e_{m+1}^F(k)$ are already computed once the current interference estimate $\hat{i}(k)$ is computed and is used as the input to the QRD-LSL interpolator. Meanwhile, the interpolation error $e_{p,f}^I(k-f)$ generated from the QRD-LSL interpolator can be used to compute the interpolated interference estimate $\bar{i}_{p,f}(k-f)$ with f units of delay, referred to herein as *interference interpolation*, by $\bar{i}_{p,f}(k-f) = \hat{i}(k-f) - e_{p,f}^I(k-f)$. Notably, $\bar{i}_{p,f}(k-f)$ is a more accurate version of the interference estimate than its prediction counterpart $\bar{i}_M(k) = \hat{i}(k) - e_M^F(k)$ due to the fact that interpolation more effectively utilizes the correlation between the nearest neighboring samples than its prediction

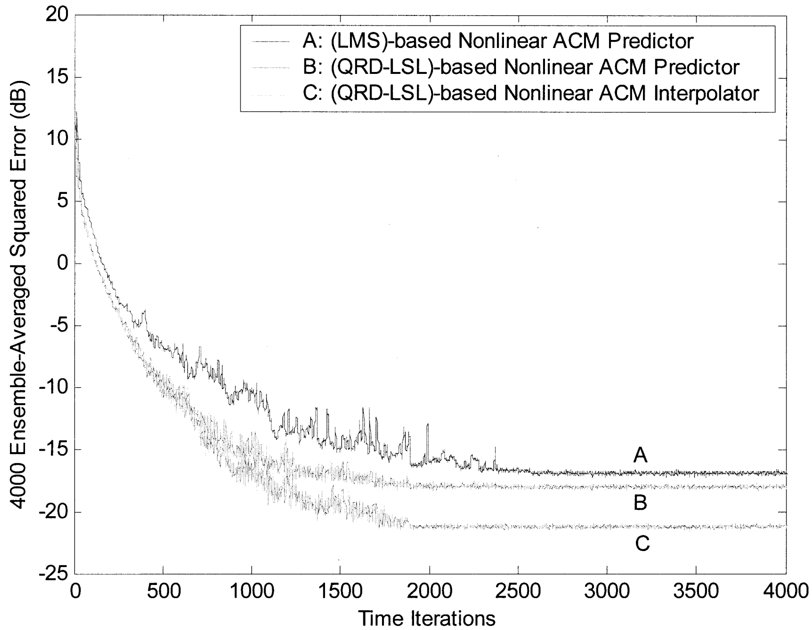

Fig. 2. Learning curves for six users with an AR interferer. System parameters: input SNR $= -20$ dB; filter order $M = 10$ for both predictors and $(p, f) = (5, 5)$ for interpolator; forgetting factor $\lambda = 0.965$ for QRD-based filters. The tap-weight update of the LMS-based nonlinear ACM prediction used in our simulations is $\mathbf{a}_{m+1}(k) = \mathbf{a}_{m+1}(k-1) + \mu(k)\rho[\varepsilon(k)]\hat{\mathbf{i}}_{m+1}(k-1)$, where $\mu(k)$ is given by $\mu(k) = \mu(0)/[r(0) + r(k)]$ and $r(k)$ is an estimate of the input power obtained by $r(k) = \beta r(k-1) + (1-\beta)\|\hat{\mathbf{i}}_{m+1}(k-1)\|^2$, in which $0 < \beta < 1$ is chosen to yield a compromise between the prediction accuracy and the tracking capability.

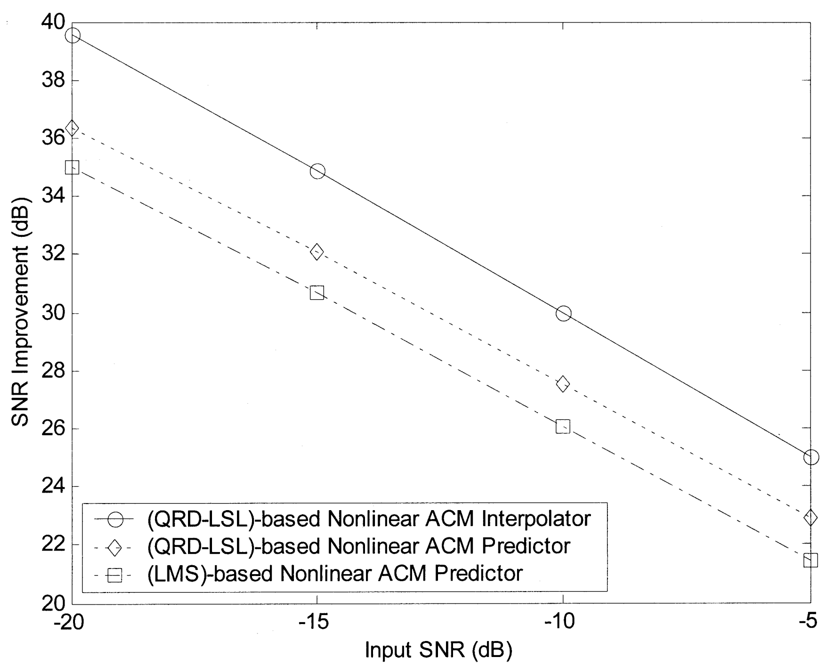

Fig. 3. SNR improvements as a function of input SNR for single- and multiuser (ten users) with an AR interferer. System parameters: filter order $M = 10$ for both predictors and $(p, f) = (5, 5)$ for interpolator; forgetting factor $\lambda = 0.965$ for QRD-based filters.

counterpart. Accordingly, a greater signal-to-noise ratio (SNR) improvement can be achieved by using interpolation as compared to that by prediction.

Once the regression coefficients $g_m(k)$, $m = 0, 1, \ldots, M-1$, are computed, the *a priori* interference prediction, at time $(k+1)$, from the output of the QRD-LSL predictor can be computed by $\bar{i}_M(k+1) = \mathbf{g}_M^T(k)\mathbf{e}_M^B(k) = \sum_{i=0}^{M-1} g_i(k)e_i^B(k)$, where $\bar{i}_M(k+1)$ represents the interference prediction of $\hat{i}(k+1)$, based on the *old* least squares estimate of the regression coefficients. Next, the *a priori* interference prediction is fed back and is subtracted from the received signal $z(k+1)$ to produce the interference estimate $\hat{i}(k+1)$ at time $(k+1)$ through the nonlinear transformation shown in Fig. 1. The resulting interference estimate $\hat{i}(k+1)$ is then used as the input to the QRD-LSL interpolator, subsequently generating the *a priori* interference prediction $\bar{i}_M(k+2)$. The same procedure continues recursively.

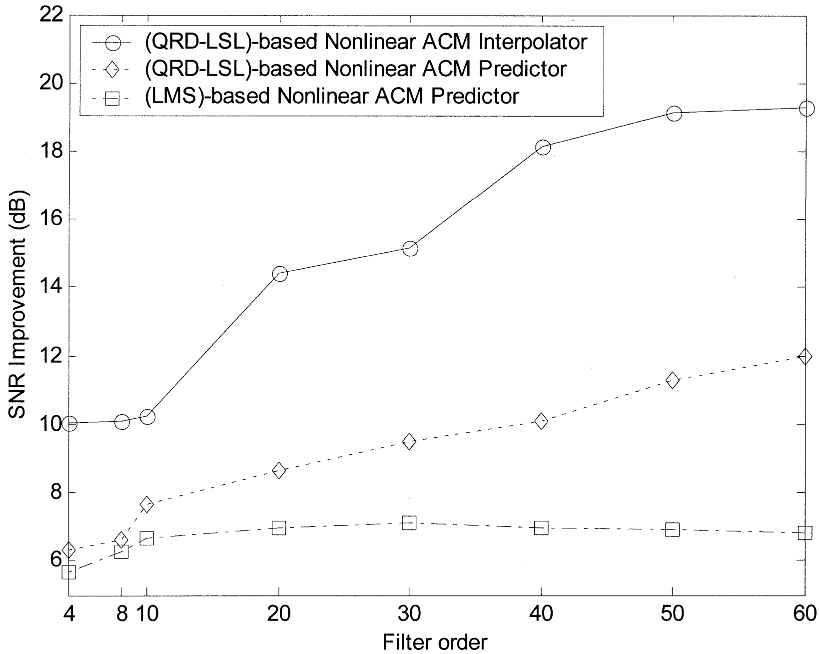

Fig. 4. Effect of the filter order on SNR improvements achieved by the three filters with a digital NBI of $m = 4$. System parameters: input SNR $= -20$ dB; filter order M for predictors and $p = f = M/2$ for interpolator; forgetting factor $\lambda = 0.965$ for QRD-based filters.

The prediction error $\varepsilon_M(k)$ of order M can then be computed as $\varepsilon_M(k) = z(k) - \bar{i}_M(k) = z(k) - [\hat{i}(k) - e_M^F(k)]$, while the interpolation error of order (p, f) can be computed as

$$\begin{aligned}\varepsilon_{p,f}^I(k-f) =& z(k-f) - \bar{i}_{p,f}(k-f)\\ =& z(k-f) - \left[\hat{i}(k-f) - e_{p,f}^I(k-f)\right]\end{aligned}$$

where both $e_M^F(k)$ and $e_{p,f}^I(k-f)$ are already computed by the QRD-LSL predictor and QRD-LSL interpolator, respectively. Notably, both $\varepsilon_M(k)$ and $\varepsilon_M^I(k-f)$ represent the estimates of the SS signal by employing the QRD-LSL predictor and QRD-LSL interpolator. They can be used to compute the SNR improvement, which is a performance measure commonly used to verify the interference rejection filters. Table I summarizes the (QRD-LSL)-based nonlinear ACM interpolation algorithm.

IV. Simulation Results

Computer simulations are performed to evaluate the performance of the proposed interpolator when the NBI is modeled as an AR process, narrow-band digital communication signals, and tonal signals for unknown interference statistics (with the noise power being held constant at $\sigma_n^2 = 0.01$). The AR interferer was obtained by passing white noise through a second-order infinite impulse response filter with both poles at $z = 0.99$. The rate of convergence and SNR improvement are compared using the LMS-based nonlinear ACM predictor [3], (QRD-LSL)-based nonlinear ACM predictor, and (QRD-LSL)-based nonlinear ACM interpolator. The learning curves in Fig. 2 are generated by ensemble averaging $[s(k) - \varepsilon_M(k)]^2$ (for predictors) and $[s(k-f) - \varepsilon_{p,f}^I(k-f)]^2$ (for interpolators). Fig. 3 reveals that the SNR improvement of the three filters is independent of the number of users and the (QRD-LSL)-based nonlinear ACM interpolator consistently provides more than around a 4.5 dB SNR improvement over the LMS-based ACM predictor. An NBI can also be modeled as a digital communications signal with a data rate much lower than the SS chip rate [8]. A system of one SS user and one digital NBI can be viewed as a virtual CDMA system in which the digital NBI can be regarded as $m{+}1$ virtual users [9]. A Gold code of length 31 is used as the spreading code. Fig. 4 shows the effect of the filter order M on SNR improvements achieved by the three filters. In this figure, increasing filter order results in higher SNR improvements for both (QRD-LSL)-based ACM predictor and interpolator until $M = 60$ when the SNR improvements for both filters appear to become steady. In contrast, the SNR improvement for the LMS-based ACM predictor remains roughly the same as the filter order is increased. The difference in SNR improvement between the (QRD-LSL)-based filters and the LMS-based predictor as the filter order is increased is perhaps because, as mentioned in Section III, LSL filters may be especially suited for suppressing orthogonal components of the NBI (notably, the signature waveforms of the $m{+}1$ virtual users are mutually orthogonal) in complex jamming environments, owing to the exact decoupling property of the LSL interpolator (predictor). Besides, the potential increase in the SNR improvement of the LMS-based ACM predictor as its filter order is increased may have been offset by a large excess mean square error (EMSE) of the LMS algorithm. The EMSE of the LMS-based algorithm is known to be proportional to the filter order.

Fig. 4 also indicates that the use of the (QRD-LSL)-based ACM interpolator can increase the SNR improvement of the LMS-based ACM predictor by more than 12 dB for a large filter order. This large gain is highly significant in practice for reducing the probability of error of the (QRD-LSL)-based ACM interpolator used in suppressing the digital NBI. Similar results can be seen in Fig. 5, in which the NBI is modeled as a multiple tone that consists of the sum of 20 pure sinusoidal sig-

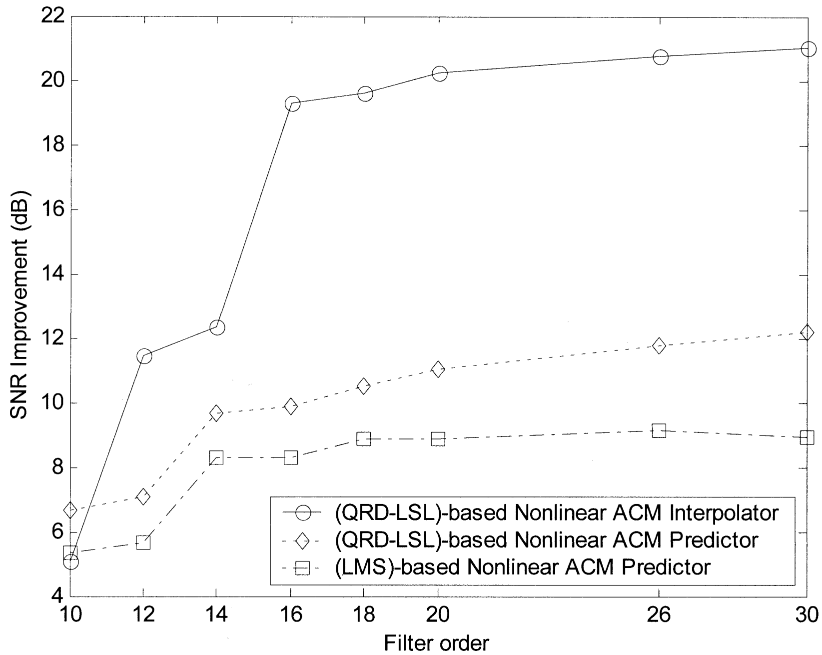

Fig. 5. Effect of the filter order on SNR improvements achieved by the three filters with a multiple tone interferer. System parameters: input SNR $= -20$ dB; filter order M for predictors and $p = f = M/2$ for interpolator; forgetting factor $\lambda = 0.965$ for QRD-based filters.

nals and is expressed as $i(k) = \sum_{m=1}^{20} A_m \cos(\omega_m k + \theta_m)$, where the amplitudes $\{A_m\}$ are selected to be identical and the phases are uniformly distributed on the interval (0, 2π). The 20 tones used for the NBI are equally distributed in four nonoverlapping frequency bands and cover 32% of the frequency band occupied by the SS signal. $\{A_m\}$ is chosen such that the input SNR $= -20$ dB.

V. Conclusions

This paper develops a (QRD-LSL)-based nonlinear ACM interpolator for NBI suppression in DS-CDMA systems. The complexity per update of the proposed interpolator is O(M), where M is the filter order. The (QRD-LSL)-based nonlinear ACM interpolator outperforms the LMS-based nonlinear ACM predictor in terms of the rate of convergence and SNR improvement when the NBI is modeled as an AR process, tonal signals, and narrowband digital communication signals. Owing to the order-recursive structure of the QRD-LSL interpolator, the proposed (QRD-LSL)-based nonlinear ACM interpolator may effectively suppress the NBI of fast time-varying bandwidth and an unknown number of frequency bands that requires different filter orders to achieve optimum results. The proposed (QRD-LSL)-based nonlinear ACM interpolator appears to be suitable in suppressing NBI in CDMA systems since each stage of the LSL interpolator adapts to suppress an orthogonal component of the NBI.

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